EVALUATION OF B1 RECEIVE NON-UNIFORMITY CORRECTION TECHNIQUES FOR QUANTITATIVE MUSCULOSKELETAL NMR IMAGING.

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1. Introduction: To be able de detect early pathological changes with high sensitivity, precision and reproducibility in diseased muscles, one needs to turn to truly quantitative imaging protocols. Unfortunately, inhomogeneities of static and rotating (B1) transmit and receive fields are an obstacle to the development of the muscle quantitative imaging concept. Conventional normalization techniques rely on the assumption that the signal is homogeneous inside each tissue [1]. Such an assumption is not valid when dealing with pathological cases. In the present work we compared three different approaches that address this issue by considering only the subcutaneous fat region to compute the B1 receiver field. These approaches are based on sum of cosine function modeling, sum of Legendre polynomials modeling and normalized convolution. The comparison was performed on 3pt Dixon volumes acquired with 2 different coil types.

2. Theory: A convenient way of designing a correction method consists in modeling the intensity non uniformity as resulting from a smooth multiplicative field. Hence we can write : $I(v) = U(v)B(v) + n(v)$ where $v=(x,y,z)$ refers to a voxel location, I the observed NMR volume, U the uncorrupted one, B the non uniformity field and n the noise. Estimation techniques using sum of Legendre polynomials [2] or cosine functions [3] were adopted thanks to their ability to approximate low frequency functions. In spite of their good performance they fail to estimate correctly the B1 receive non-uniformity due to lack of information in the muscle tissue. In [4], the authors showed that when the hypothesis of tissue homogeneity is valid only for one tissue, an additional constraint that penalizes high oscillations of B function is necessary. In the present work, we also showed in the experimental section that even by using Legendre polynomials, an additional term that reduces the variation of the non-uniformity function is required.

Legendre Polynomials and cosine model with total variation constraints Sum of Legendre polynomials as well as cosine functions can reasonably approximate a low frequency function such as the B1 receive non-uniformity function. Thus we can write $B(v) \approx \sum_{k=1}^{M} h_k f_k(v)$ where (f_k is the k^{th} element of the 3D cosine basis or the 3D Legendre polynomials family). The function B is completely defined when the set of coefficients h is known. Under the assumption that the signal in the subcutaneous fat region (noted Ω_{sf}) is uniform and that it can be approximated by its mean value (called μ_f), the set of h coefficient is obtained by minimizing

$$E(h) = \sum_{v \in \Omega_{sf}} \left\| I(v) - \mu_f B(v) \right\|^2 + \lambda \sum_{v \in \Omega} \left\| \nabla B(v) \right\|^2$$ The function is a combination of two terms the first is the uniformity constraint in the region of the subcutaneous fat and second concerns the amount of oscillations inside the image domain. The coefficient λ is the tradeoff coefficient between the two constraints.

Normalized Convolution Normalized convolution is a non parametric interpolation technique that was used in [5] in the context of non uniformity correction. For our comparative study we implemented it in an iterative manner. Based on the observations that the signal is uniform on the subcutaneous fat we computed an estimate of the non-uniformity values in this region. Next using normalized convolution, we propagated iteratively the non uniformity field values inside the muscle region.

3. Material and Methods Toward evaluating the performance of the different techniques described previously, we acquired several data sets in different experimental conditions. The data sets are composed of 3D volumes of thigh of 13 healthy subjects acquired with a 3T Siemens scanner and using 3pt Dixon sequence (TR=10ms, TE1=2.75 ms TE2=3.95 ms TE3=5.15 ms, rf flip angle =3°). The data set was acquired using a CP extremity coil (n=6) and a body matrix coil (n=7).

Processing First, we estimated the B1 transmit non-uniformity using the AFI technique [6] to correct the Dixon water fraction volume and fat fraction volume. Next, we applied the three different techniques previously described, using the fat volume and the subcutaneous fat binary one to estimate the B1 receive non-uniformity.

Evaluation criteria To evaluate the performance of the different techniques, we considered the coefficient of variation (CV) as a criterion. For healthy subjects, we determined the CVs of the subcutaneous fat in Dixon fat images and inside the muscles region using the Dixon water images. In figure 1, the CV decreases are presented as percentages of the CV values before correction.

4. Results and discussion Table1 show the performance of each method for both coils: C1 (Body matrix) and C2 (CP extremity). Adding a total variation constraint was necessary when using Legendre polynomial models too because CV increased inside the muscle region for λ=0. Regarding normalized convolution, figure 1 shows that even though it achieved higher performance in the subcutaneous fat area, it failed to estimate correctly the non uniformity field values inside the muscle region with both types of coil. This confirmed that non parametric techniques were not adapted when the region of missing information is large with respect to the available normalization samples. On the other hand, cosine function based model as well as Legendre polynomial yielded similar performances for both coil types (Non parametric Kruskal-Wallis tests for Body Matrix p=1 and CP extremity coil p=0.65). Figure 2 displays a Dixon-based muscle fraction of an axial slice through the thigh and illustrates the homogeneity improvement obtained with the three methods we compared. In conclusion, the cosine functions and Legendre polynomial methods were the most appropriate ones to correct receiver non uniformity field starting from the homogeneity assumption on one specific tissue. This step is a prerequisite for quantitative analysis of musculoskeletal NMR images.

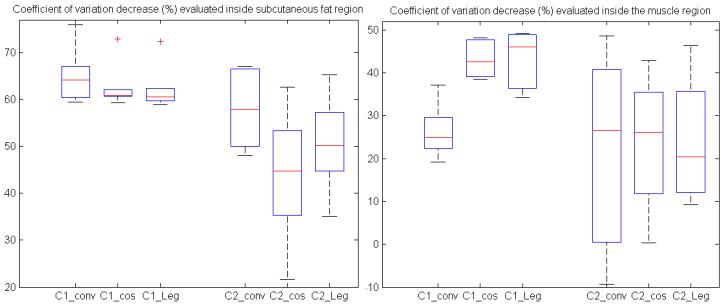

Fig.1 *Box plot of the percentage of decrease of coefficient of variation using different coils. (C1= body matrix, C2= CP extremity, conv =normalized convolution, cos=cosine model proposed in [3] (M=4, λ =1000), Leg = Legendre model (M=4, λ =500).*

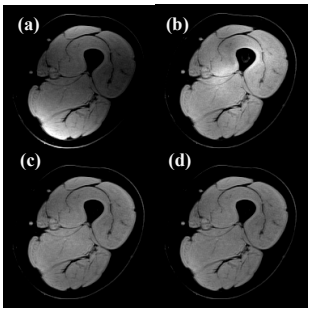

Fig.2 *Axial slice through the thigh in Dixon based water fraction. (a) No correction (b) norm conv (c) Cosine (d) Legendre.*

	CV mean C1	CV mean C2
F_init	0.350	0.181
F_conv	0.123	0.074
F_cos	0.141	0.103
F_Leg	0.134	0.095
F_Leg*	0.102	-
M_init	0.222	0.130
M_conv	0.166	0.103
M_cos	0.130	0.100
M_Leg	0.129	0.098
M_Leg*	0.794	-

Tab.1 *Mean value of the coefficient of variation for both coils (C1&C2) before correction (init) and after correction. Leg*=Legendre Poly model with $\lambda = 0$. (F= fat and M= muscle).*

References : [1] B.Belaroussi et al, Med, Image Analysis, 2006. **[2]** M.Styner et al, IEEE Trans Med Imaging, 2001. **[3]** O. Friman, et al, in ISMRM, 2009, **[4]** N.Azzabou et al in ISMRM 2010. **[5]** O. Friman, et al, in ISMRM 2008. **[6]** V.L. Yarnykh,Magn Reson Med, 2007.